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THE QUALITY AND USER ACCEPTANCE OF DECISION ANALYSIS PERFORMED BY COMPUTER VS. ANALYST

BY

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20. ABSTRACT (Continue on reverse side if necessary and identify by block number)

The state-of-the-art in decision software is at a level of data storage, display, and computation as an aid to a sophisticated user. Almost certainly, the emerging generation of decision software will be designed to perform a larger range of analyst functions. We have focused on two potential problems challenging the computerization of decision analysis, and on assessing the extent to which these problems can be overcome. First, to what extent can the often ill-defined art of structuring be transformed into software; and secondly, to what extent is past consumers' satisfaction with

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Although the analyst attribute sets were more often judged more complete and better in overall quality, the MAUD 3 attribute sets were more often judged more nearly independent, both logically and valuewise. Furthermore, the attribute sets of each pair with the greater number of dimensions was overwhelmingly chosen as being more complete, less independent, and of higher quality than the other attribute set. Interestingly, judgments of overall quality were virtually identical to those of completeness.

We found that MAUD 3 is not truly "stand-alone". In particular, our subjects needed at least some instruction in the attribute elicitation phase of the program. We also found that most subjects are unable to answer the brlts weighting question properly; uninstructed responses exhibit a sort of risk aversion that renders the weights virtually meaningless.

SUMMARY

The state-of-the-art in decision software is at a level of data storage, display, and computation as an aid to a sophisticated user. Almost certainly, the emerging generation of decision software will be designed to perform a larger range of analyst functions. We have focused on two potential problems challenging the computerization of decision analysis, and on assessing the extent to which these problems can be overcome. First, to what extent can the often ill-defined art of structuring be transformed into software; and secondly, to what extent is past consumers' satisfaction with decision analysis a function of the formal methods and procedures of the theory and rationale of decision theory, and to what degree do other factors such as personal interaction and the establishment of a rapport account for client approval?

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INTRODUCTION

Computerized decision aids have become an indispensible tool in decision analysis. The majority of the early aids were designed to perform such functions as data storage, information display, and sensitivity analysis. For example, Decisions and Designs, Inc. developed several aids, largely for performing rapid assessment and sensitivity analysis in simple decision structures involving multiattribute alternatives (EVAL), uncertainty (DECISION), or both (OPINT). Such aids typically require the services of a decision analyst, or a team of analysts, including one who directs the execution of the program. The primary emphasis of these decision aids is on augmenting the efficiency and power of the analyst, and not on the direct automation of critical analyst functions, such as option invention, problem structuring, or parameter elicitation.

We expect the development of decision aids to go in two directions. First, the aids will become less dependent on the presence of a decision analyst. Second, aids will be tailored to more substantive problem areas using perhaps generic problem structures and expertise or data bases in combination with standard decision analysis methodology.

The computerization of decision analysis in these directions faces numerous problems. The purpose of the present paper is to focus on two such problems. First, most of what goes on in decision analysis, especially during early phases of option generation and problem structuring, is more accurately described as "art" than as "science." To what extent can this often ill-defined art be defined by precise formal algorithms that can be translated into software?

Secondly, past consumers of decision analysis have expressed both satisfaction with the process and acceptance of the conclusions of analyses. To what extent is this satisfaction and acceptance a function of the formal methods and procedures embodied in decision theory and the technology of decision analysis, and to what extent do other factors such as personal interaction and the establishment of a rapport account for client approval?

We will first discuss empirical research and speculation bearing on the issues of problem structuring, option invention, user satisfaction of decision analysis procedures, and user acceptance of decision analysis recommendations. Following this brief review, we will describe an exploratory study comparing an analyst-run decision analysis with a similar one conducted by computer.

Option Generation and Problem Structuring

Most algorithms for option generation and problem structuring require certain parts of the problem to be given (e.g., goals), and then derive other parts (e.g., alternatives) from the given structure. Pearl (Note 1) first proposed a procedure for option generation, in which alternatives are sought which achieve individual goals, while being unconstrained with respect to the remaining goals. Presumably this procedure sets the option generator/decision maker free from the highly constrained situation under which options are usually sought, leading both to a larger number and to a better quality of options. Pearl, Leal, and Seleh (Note 2) recently developed a structuring program that utilizes this method, called GOal-Directed DEcision Structuring System (GODDESS).

In a recent behavioral study, Pitz, Sachs, and Heerboth (1980) tested Pearl's "means-ends analysis" approach to option generation. College students were given a personal decision problem scenario, and asked to generate as many reasonable alternatives as possible. Three groups were given a list of objectives (attributes) and asked to generate alternatives that satisfied the objectives one at a time, two at a time, or all simultaneously. Two groups were simply given example alternatives (either categorized or randomly displayed); one group was told to think of possible objectives relevant to the decision problem, and one group was told only to generate alternatives. Although the mean group differences were small, there was a tendency for the single attribute maximizers to produce more reasonable alternatives and for the multiple attribute maximizers to produce fewer alternatives.

Gardiner (1977) proposed the notion of "decision spaces" as an aid for the general problem of deciding when to stop looking for more alternatives. Beta probability density functions (pdfs) are constructed on each attribute to model the distribution of available or potential options over that attribute. Using the MAU model, the single attribute pdfs can then be aggregated into a single pdf over the overall value. Such a pdf puts given options into the perspective of past or future options. Alternatives should be eliminated if their value falls in the lower tail of the distribution. If few or no alternatives fall in the upper tail, more options need to be generated. In addition, improvement of options is likely to occur in those attributes on which most options score in the middle or in the lower tail of the pdf. Thus, Gardiner (1977) suggests formal rules for deciding how to eliminate and to improve options. There has been no behavioral experiment in the context of decision spaces.

Leal and Pearl (1977) discuss an (unnamed!) interactive program for eliciting problem structures in the form of action-event decision trees. The software employs an algorithm for expanding sensitive portions of the structure and pruning insensitive portions, based on provisional intermediate values. In this case the structuring process is derived from a specification of the options and early skeletal elements of the structure.

Humphreys and Wooler (Note 3) describe a set of "structuring heuristics" for generating objectives and goals in a multiattribute evaluation problem. One procedure, implemented in a computer program called "Multi-Attribute Utility Decomposition" (MAUD, Humphreys and Wisudha, Note 4) derives attributes from a predetermined specification of options. The user is asked to identify the opposite poles of dimensions along which the available options differ. Humphreys and McFadden (1980) tested their attribute assessment procedures in several applications, concluding that "where MAUD was able to aid people it did so through the reduction of goal confusion, and through consciousness raising about the <u>structure of value-wise importances</u> of attributes possessed by choice alternatives".

Pitz, Sachs, and Brown (Note 5) report an empirical test of a technique for generating problem structures and options simultaneously. After an initial cursory listing of options and goals, the decision-maker is told to carefully consider each goal separately, and to try to identify other options that might be helpful in fulfilling individual goals. (This part is similar to the option generation procedure tested by Pitz, Sachs, and Heerboth, 1980). Next, the decision maker is told to consider each option, including the newly generated ones, and is required to project possible outcomes of each. The decision maker is asked to identify additional goals that would be satisfied by projected desirable outcomes and undermined by undesirable outcomes. Pitz, et al. (Note 5) report that college students faced with a personal planning problem produced more choices and more goals with this procedure than with three alternative methods.

It should be apparent from our review that computerization of the structuring part of decision analysis is still in its infancy. The basic idea of fleshing out a structure by building on initial skeleton elements and using decision analytic relations seems promising. So far, this idea has been mainly used to formalize the derivation of options from goals, and the derivation of attributes from options. It is conceivable that this technique could be extended to hypothesis generation and act-event structuring as well.

User Satisfaction and Acceptance of Recommendations

There is relatively little data from controlled experiments on our second problem relevant to the computerization of decision analysis: user satisfaction with the process of decision analysis and acceptance of recommended courses of action. Fischhoff (1981) speculates on sources of resistance to personal decision analysis:

> People who need decision analysis may reject it (1) because they are personally threatened by having to face and acknowledge their own doubts and desires, (2) because they wish to avoid decision analysis' full public disclosure requirement, (3) because they feel uncomfortable and incompetent to deal with probabilities and multi-attribute certainty equivalents, (4) because they are afraid to innovate.

Presumably, the anonymity of computerized decision aids could prove to be a major benefit with regard to the first two concerns voiced by Fischhoff. The absence of another person with whom to ask questions and seek reassurance could prove to be a disadvantage with respect to his last two concerns. Presently, we have no good data -- only speculation.

On the issue of user acceptance of the "best alternative" suggested by a decision analysis, Fischhoff (1981) states:

> Once a decision analysis has been performed, its bottom-line recommendations may be rejected because they are viewed as the output of numerical mumbo-jumbo which has no intuitive appeal and cannot be readily justified to superiors, subordinates, constitutents, etc.

Fischhoff is clearly focusing on the issue of trust here. Whether a computer or human analyst is viewed as more trustworthy will certainly vary with the situation; a good deal of the variance is probably accounted for by the reputation of the decision aid (analyst or computer) and the attitudes of the decision maker and those affected by the decision. In a personal decision context, much would depend upon the decision maker's personal knowledge of the aid (either analyst or computer) gained through past experience.

Christen and Samet (Note 6) report some provocative data on the issue of decision maker acceptance of recommendations arrived at by OPINT, Decisions and Designs, Inc.'s computer aid for the rapid screening of decision options. In their laboratory evaluation, experienced naval intelligence analysts were presented with a background scenario and intelligence summaries, and required to diagnose enemy military plans either with the assistance of OPINT or not. A set of "correct" diagnoses was determined independently for each stimulus intelligence report. OPINT's recommendations to aided officers outperformed the unaided officers by making about 33% more correct decisions. But the aided officers frequently disagreed with OPINT, leading to essentially equal performance between aided and unaided officers. Apparently the lack of confidence in the aid produced a substantial decrement in the officers' performance. Since OPINT requires the services of a decision analyst, many questions remain unanswered. In particular, would a similar decision aid administered by an analyst without a computer have produced more or less rebellion from the naval officers? Would a user-oriented stand-alone version of OPINT have instilled more or less confidence?

The Present Experiment

We sought to directly compare multi-attribute utility analyses performed by an analyst and by a computer program. We selected MAUD 3, an interactive MAUA program "designed to work in direct interaction with the decision maker, without a decision analyst, counselor, or other 'expert' as intermediary"(Humphreys and McFadden, 1980). Each college student subject interacted with both an analyst and MAUD 3 at different times. The experiment afforded four critical comparisons of the analyst and computer sessions, related to differences in: (1) final recommendations, (2) correspondence of final recommendations with intuition (holistic assessments), (3) the number and quality of attributes, and (4) stated satisfaction with the process and confidence in the results. The repeated observations (within subjects) design chosen offers the most sensitive tests of differences between the MAUD 3 and analyst interactions, especially with regard to problem structuring.

All decision problems were multi-attribute evaluation problems generated individually by our subjects. Although Pitz and his colleagues have performed several value experiments with college students demonstrating the viability of hypothetical scenarios (e.g., roommate difficulties, Pitz, Sachs, and Heerboth, 1980; apartment choice, Pitz, Heerboth, and Sachs, 1980; and vacation plans, Pitz, et al., Note 5), we elected to elicit personal problems that were currently important for each individual subject. (Each of the three examples above was proposed by at least one of our subjects.) We felt that questions of user satisfaction and confidence could only be addressed in a real context tapping personally relevant values[1].

Since MAUD 3 does not provide any mechanisms for option generation, all options were generated prior to either decision analytic session. So as to increase our ability to detect differences in the recommendations of the two analyses and their correspondence with intuition, only feasible, highly-viable (non-dominated) alternatives were allowed. Finally, in order to maintain maximum sensitivity to differences in model recommendations, we sought to reduce random judgmental errors by requiring that the subject possess a minimal level of knowledge of the proposed choice alternatives.

METHOD

Design Overview

Thrity-five college students underwent two versions of multi-attribute utility analysis in two experimental sessions, each lasting from 1 to 3 hours. The complete protocol of the experiment is presented chronologically in Table 1.

Insert Table 1 about here

All subjects identified an evaluation problem at the beginning of the first session that (1) was personally important and relevant, (2) involved four or more viable alternatives, and (3) required information that was readily accessible. Twenty-four subjects interacted with the computer program (MAUD 3) during the first session, and with one of five human analysts during the second session; the remaining eleven subjects first interacted with a human analyst, and then with MAUD 3. Before and after each MAUA interaction, subjects provided various judgments, including (1) "holistic ratings" of the choice alternatives, (2) rankings of different vectors of alternative ratings, and (3) self-report measures of the usefulness of the MAUA technique used.

Following all experiment sessions, each subject's pair of attribute sets (MAUD 3 and analyst) was presented (blindly) to three of the five analysts, along with a generic description of the corresponding choice alternatives (e.g., "college majors"). Analysts made quantitative judgments concerning the completeness, logical independence, and value independence of the attribute sets, as well as their "overall" or "global" quality.

Subjects

Sixty-seven college students (31 females, 36 males) enrolled in an introductory psychology course at the University of Southern California were interviewed. Of these, 35 (52%) were able to identify a multiattribute evaluation problem that met the requirements of personal relevance and accessible information, and

TABLE 1

Experiment Protocol

Session 1
Induction Interview: Problem specification, listing of alternatives, and subject screening
Pre-MAUA holistic ratings of alternatives* (H1)
Interaction with MAUD 3 or analyst: Multiattribute values (A1 and E1) are derived from assessed weights and equal weights, respectively
Post-MAUA holistic ratings of alternatives* (H2)
Self-report ratings of the interaction**
Ranking of Session 1 alternative ratings sets (H1, H2, and A1; also E1 for MAUD 3 session)***
Session 2 (approximately one week later)
Pre-MAUA holistic ratings of alternatives* (H3)
Interaction with MAUD 3 or analyst: Multiattribute values (A2 and E2) are derived from assessed weights and equal weights, respectively
Post-MAUA holistic ratings of alternatives* (H4)
Self-report ratings of the interaction**
Ranking of Session 2 alternative rating sets (H3, H4, A2; also E2 for MAUD 3 session)***
Forced choice between most preferred set of alternative ratings from Session 1 and from Session 2
Forced choice between assessed weight model composites from Session 1 and from Session 2 (A2)
Ordinal judgment of superiority between MAUD 3 and the analyst on the self-report items
Debriefing: Discussion of MAUD 3 and analyst procedures and discrepancies among holistic ratings and MAUA recommendations

TABLE 1 (continued)

*Each subject listed his/her choice alternatives from most preferred (assigned an anchor of 100) to least preferred (anchored at 0). Subjects were told that an alternative (X) should be rated 50 if the increment in desirability from the worst alternative to X was equivalent to the increment in desirability from X to the best alternative.

**Each subject rated (from 1 to 10) the degree to which he/she:
(1) had discovered new aspects of the problem via the MAUA interaction;
(2) felt comfortable during the interaction;
(3) thought the MAUA had helped to solve the problem;
(4) trusted the MAUA to recommend the "best" alternative; and
(5) would desire to use the particular MAUA technique for future decision problems.

***Model composite evaluations derived from assessed weights (and equal weights for MAUD 3 sessions) were normalized to the same 0-100 scale as the holistic ratings by subtracting the lowest rating from all ratings, dividing by the difference between the lowest and the highest rated alternative, and multiplying by 100. Each subject rank ordered the three sets of alternative ratings (four sets for MAUD 3 sessions) in terms of his/her agreement with the ratings (and implied orderings). The source of rating sets was not explicitly identified.

included at least four viable alternatives. These 35 students (22 females, 13 males) served as subjects; the rest were dismissed. All 67 students received credit toward a course requirement proportional to the number of hours of participation.

Problem Specification

One male experimenter conducted all 67 induction interviews in a private office, each lasting from approximately 15 minutes to 1½ hours. Each interview began with the subject reading a brief description of the experiment, outlining the purpose of the two experimental sessions. Subjects were told that the first step would be to identify a decision problem that was personally important and currently relevant. Hypothetical choice situations, decisions that had already been made and acted upon, and problems whose outcomes had no clear, direct effect on the subject were discouraged by the experimenter, and ultimately rejected. The experimenter stressed that the problem should involve options with distinctly positive and negative aspects. In particular, a proposed alternative to a decision problem was rejected if the subject admitted not really knowing very much about the alternative, or if the subject felt that the alternative, although a possible course of action, was not something he/she could envision ever really doing.

The final product of the induction interview, for the 35 subjects who developed choice dilemmas meeting the experimental criteria, was a list of at least four and not more than eight well defined alternative courses of action. Problems included choosing among majors (at USC) (11), colleges to which to transfer (9), places to live (in the Los Angeles area) (6), careers (4), travel plans (2), automobiles (1), sports activities, (1), and strategies for handling a roommate difficulty (1).

Most of the 32 rejected subjects identified a choice dilemma decomposable as an MAU evaluation problem, but that failed to meet one or more experimental requirements. In particular, many male students were reluctant to consider as many as four viable alternatives, insisting that they had "narrowed" problems down to only two (usually) or three alternatives. As a result, the rejection rate for males (64%) was significantly higher than that for females (29%), who often indicated little or no pre-screening of alternatives.

MAUD 3 Sessions

Computer operation instructions. All MAUD 3 sessions were monitored by the same experimenter who conducted the induction interviews and collected all judgments outside of the MAUA interactions. After providing pre-MAUD 3 holistic ratings of the alternatives, subjects were led to a separate room near that of the experimenter. Subjects were seated at a desk, on top of which sat an IBM 5110 minicomputer, an IBM 5103 printer, and a cathode ray tube (CRT) monitor. MAUD 3 was pre-loaded into the computer storage before subjects arrived, and all sessions began with the MAUD 3 request for a session name. Subjects were given a standard introduction to familiarize them with the keyboard, CRT, and printer.

Subjects were told that MAUD 3 would eventually ask a question beginning: "Do you want to investigate your preferences?" The subject was instructed to stop when that question appeared, and to report to the experimenter's office. Subjects were told also that the experimenter would be available in his office prior to the "stop" question, should there be a problem, but that he/she should attempt to communicate with MAUD 3 without additional help.

Elicitation of attributes and single-dimension values. Details of the MAUD 3 assessment can be found in Humphreys and McFadden (1980) and Humphreys and Wisudha (Note 4). Briefly, MAUD 3 begins by recursively eliciting attributes, assessing single-dimension value functions, and checking for correlations between pairs of value dimensions. Endpoint descriptions of attributes are determined by asking how triads of alternatives differ, or by asking for the endpoints directly. Single-attribute value functions are assessed by placing each alternative on a nine-point rating scale (anchored at the elicited endpoints), determining an "ideal point" along the 9-point range, and normalizing under an assumption of piece-wise linearity. When significant correlations between these normalized value functions are detected, the subject is given an opportunity to combine the two dimensions under a single heading; otherwise they remain in the analysis as separate attributes. After the addition of each attribute (beyond the first three), MAUD 3 allows the subject to review the attribute descriptions, single-attribute value ratings and ideal points, and normalized single-attribute values. After MAUD 3 finished the attribute elicitation, the experimenter asked whether subjects were sure that all attributes were included. About half of the subjects added attributes at that point. Subsequently, subjects performed the brlts assessment of scaling parameters (weights). No subject wished to assume that the various attributes were all equally important in determining preference.

Assessment of weights. MAUD 3 assessed scaling parameters (importance weights) under an assumption of additive utility independence using a version of the basic reference lottery tickets (brlts) procedure. (For details, see Humphreys and Wisudha, Note 4; for more on brlts, see Keeney and Raiffa, 1976). For n attributes, MAUD 3 presents n-1 brlts questions, consisting of a choice between a "moderate" sure thing (alternative best on one dimension and worst on one dimension) and a gamble in which an "excellent" outcome (alternative best on both dimensions) results with probability p, and a "poor" outcome (alternative worst on both dimensions) results with probability 1-p. The two dimensions chosen for each brlts question are determined by the correlational structure of the normalized single-attribute values and earlier brlts judgments. The algorithm is designed to include every attribute in at least one brlts question, and to include more important attributes in more brlts questions than less important attributes. An attempt is made to select early attribute pairs that are positively correlated, thus creating easily imagined alternatives in the gamble, but not in the sure thing. Later attribute pairs, more critical to the weight assessment, are selected so as to bear as little statistical association as possible.

Observation of pilot subjects indicated that most subjects had trouble understanding the brlts question; in particular, subjects often became confused and frustrated at trying to keep so many pieces of seemingly unrelated information in mind at once. Further observation of pilot subjects provided with the above instruction revealed that there was a deeper problem inherent in the brlts question. Specifically, most subjects always switched their preference to the sure thing for values of p greater than .50 (usually .70 or .80) regardless of the attribute pair.

As a remedy, the experimenter explained that the standing of the sure thing alternative with respect to the gamble outcomes should be related to the relative importance of the two varying attributes. The form and content of the brlts intervention was standardized (as much as possible, given that the subject was allowed to ask questions), and kept as brief as possible. An attempt was made to keep the intervention detached from the flow of the MAUD interaction.

Once the instructions were given, the experimenter asked the subject to report to his office after the last brlts question. The experimenter left the subject alone for the remainder of the MAUD 3 session. Most MAUD 3 sessions lasted between 1 and 2 hours.

Analyst Sessions

Five different analysts were utilized, including two research faculty, one seventh-year graduate student, and two first-year graduate students. None of the analysts had more than cursory experience with applying MAUA for personal decision problems, and the two first-year students learned of MAU ideas only a few weeks before their involvement in the study. After obtaining pre-analyst ratings, the experimenter introduced the subject to his/her analyst; this assignment was determined largely by who was "in" at the time. All analyst MAUA sessions were carried out in the private office of the analyst, with no intervention from the experimenter of any kind. Although details of the procedure varied across analysts, and even across subjects assigned to the same analyst, all sessions were similar to Edwards's (1972, 1977) Simple Multi-Attribute Rating Technique (SMART).

Like MAUD 3, the analysts determined a list of relevant attributes, elicited single-attribute values for each alternative, and assessed scaling parameters (weights). Although SMART does not suggest any specific procedure for determining relevant dimensions, retrospective discussions with analysts indicated that all had used one or more of the following methods: (1) suggestion of a particular attribute; (2) asking the "MAUD 3-like" question "How do these alternatives differ?"; (3) asking "How is alternative X attractive?"; (4) asking the subject to find one aspect on which each and every alternative is attractive; (5) asking "What attributes do you want to consider?" directly; and

(6) asking "What factors are relevant to the decision?". A distinction is made between the last two procedures since some analysts allowed the subject to include any attribute that he/she wanted, whereas other analysts stressed the requirement of relevancy, thereby screening out "unimportant" attributes or attributes with little variability.

Single-attribute values were elicited using some version of the SMART procedure, using 0-100 rating scales for eliciting single attribute utilities and ratio procedures for weight assessments. Some analysts specifically called the subject's attention to the problem of attribute ranges, explaining that an attribute with a restricted range among the alternatives at hand should receive less weight than might be the case if the range were larger. One analyst explained the concept of attribute importance in terms of "how much one would like to step from the worst available level of the attribute to the best available level"; subjects were told to reflect the desirability of this increment in their direct subjective estimates of weight. This weight assessment question is similar to that used in the so-called "swing-weight" elicitation technique.

When the session was completed, the analyst led the subject back to the experimenter's office. Most analyst sessions lasted from one to two hours.

Analyst Evaluations of Attributes

Three of the five analysts (two research faculty and one first-year graduate student) evaluated all 70 attribute sets (35 subjects X 2 analyses) in terms of (1) completeness, (2) logical independence, (3) value independence, and (4) "overall global quality". Each subject's pair of attribute sets was presented along with a generic name for the four or more alternatives evaluated. The experimenter abstracted attribute names from the endpoint labels for MAUD 3 attributes. All analyst judgments were collected blind, as analysts did not know which attribute set resulted from the MAUD 3 and which from the analyst session, nor did they know the subject/analyst source of individual attribute sets.

All analysts were given written instructions defining completeness, logical independence, and value independence. No explanation was given for "overall global quality". In addition, the experimenter met with the analysts in a group to discuss the definitions via several examples and to answer questions. The three analysts made their judgments independently over a period of several days following the meeting.

For each subject's pair of attribute sets (MAUD 3 and analyst elicited), analysts made an ordinal judgment as to which more nearly captured the relevant aspects of the generic evaluation problem (completeness), and assigned a number reflecting the ratio of the number of aspects covered by the more complete attribute set to the number covered by the less complete set. Logical independence and value independence were judged on 100 point rating scales, each anchored by the attribute set of the 70 judged least independent (assigned a 0) and the attribute set of the 70 judged most independent (assigned a 99). An attribute set is considered to be logically independent if the attribute labels do not mean the same things semantically. An attribute set is value independent if the value of an alternative on one attribute is not influenced by the alternative's value on another alternative, for all pairs of attributes. Logical independence is much weaker than value independence, since value independence implies logical independence, but the reverse is not true. Logical non-independence is one form of overlap, leading to so-called "double counting"; all such instances are examples of value non-independence. But value non-independence may arise from other causes as well. Overall judgments of global quality were also made on a 100 point rating scale, anchored by the "worst" attribute set of the 70 (assigned a 0) and the "best" attribute set of the 70 (assigned a .99).

RESULTS

We present three kinds of data analyses. In the first we examined the convergence of multiattribute models from the MAUD 3 and analyst sessions and the agreement between models and subjects' holistic judgments. The second analysis compared the user satisfaction and acceptance ratings of MAUD 3 and analyst sessions. In the third analysis, we compared the size and quality of the attribute sets generated by MAUD 3 and the analysts.

Convergence

To study convergence we calculated each subject's multiattribute utilities using single attribute value ratings from MAUD 3 and analyst sessions, coupled with either assessed weights, or equal weights. Overall, the convergence across the resulting four models is quite encouraging. The median Pearson product correlation between multiattribute utilities of MAUD 3 and analysts (using assessed weights) was .63. For 54% of the subjects the analyst and MAUD 3 assigned the highest utility to the same option. Using equal weights for both the analyst and MAUD 3 increases this convergence somewhat (median product moment correlation of .71, with 65% matching highest utility option).

Another convergence measure was the correlation between subjects' holistic ratings of the options and the multiattribute utilities calculated from the models. Table 2 shows the median Pearson correlations (ranging from .50 to .88), conditionalized on whether subjects first interacted with MAUD 3 (top half) or the analyst (bottom half). Although differences are obviously small, three minor trends are suggested. First, assessed weights had a higher correlation with holistic ratings than did equal weights in 13 out of the 16 possible comparisons. Secondly, all 8 sets of holistic ratings appear somewhat more consistent with

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Insert Table 2 about here

TABLE 2

Median Pearson Correlations between

Holistic Ratings and MAUA Values

MAUA Values	Weights	Holistic Rating From:			
		First Session		Second Session	
N=24		Pre-MAUD 3	Post-MAUD 3	Pre-analyst	Post-analyst
MAUD 3	Assessed	.55	.71	.63	.61
	Equal	.67	.63	.59	.77
Analyst	Assessed	.55	.63	.67	.77
	Equal	.58	.58	.56	.69
N=11		Pre-analyst	Post-analyst	Pre-MAUD 3	Post-MAUD 3
Analyst	Assessed	.84	.80	.79	.76
	Equal	.50	.60	.61	.62
MAUD 3	Assessed	.82	.80	.83	.88
	Equal	.73	.69	.74	.79

the model that either directly preceded or followed the rating. Thirdly, holistic ratings tended to drift towards closer agreement with the multiattribute utilities as the sessions progressed. In six of the eight cases, multiattribute models correlated more highly with the final holistic ratings than with any of the remaining three holistic ratings sets.

Table 3 shows the convergence of multiattribute models with holistic ratings in terms of the proportions of subjects whose ratings and models agreed on the most preferred option. Although the differences are small, there is a tendency for analyst derived utilities to match both the last assessed and the most preferred holistic ratings more closely than does MAUD 3. However, a comparison between subjects who received MAUD 3 first with those who interacted with the analyst first shows that MAUD 3 utilities agreed more closely with the holistic ratings that directly followed the first session than did the analyst's utilities (63% vs. 36% for assessed weights).

Insert Table 3 about here

A final measure of convergence were the subjects' blind rankings of the sets of ratings produced by holistic judgments and the models. 22% of the subjects indicated more agreement with the analyst's utilities than with holistic ratings generated either before or after the analyst session. The same was true of only 12% of the subjects in the MAUD 3 sessions. When forced to choose between MAUD 3 utilities and analyst utilities (with assessed weihgts), a slim majority (58%) indicated more agreement with the analyst's results.

In summary, we found moderately encouraging convergence across

TABLE 3

Proportion of First Choice Agreements

between Holistic Ratings and MAUA Recommendations*

Session	Weights	Holistic Rating Set		
N=24		Post-MAUD 3	Post-analyst	Most Preferred
MAUD 3	Assessed	63%	50%	58%
	Equal	50%	46%	54%
Analyst	Assessed	---	58%	67%
	Equal	---	61%	70%
N=11		Post-Analyst	Post-MAUD 3	Most Preferred
Analyst	Assessed	36%	64%	64%
	Equal	45%	64%	64%
MAUD 3	Assessed	---	55%	55%
	Equal	---	45%	45%

*Top: MAUD first; Bottom: Analyst first.

models and between models and holistic judgments. There was no clear "winner" in the comparison of MAUD 3 and analyst's convergence with holistic judgments. Many of the subtle convergence trends appeared to be due to ordering of sessions and/or to the temporal proximity of holistic judgments to the respective modeling activity.

User Satisfaction and Acceptance of MAUA

Next we analyzed subjects' expressed satisfaction and acceptance of the MAUD 3 vs. analyst sessions. The proportion of subjects rating MAUD 3 higher than the analyst, and vice versa, are displayed in Table 4 separately for males and females.

Insert Table 4 about here

Females overwhelmingly indicated a desire to use the analyst rather than MAUD 3 in future decisions and confidence that the analyst rather than MAUD 3 recommended the best option. Furthermore, females found the analyst interaction to be more helpful, more comfortable, and more effective in discovering new aspects of the problem than MAUD 3. Contrarily, males were split roughly evenly on the issue of whether MAUD 3 or the analyst brought out more new aspects of the problem or "helped" to solve the problem. In addition, males indicated a preference to use MAUD 3 rather than an analyst for future decision, despite strong agreement with the females that analyst interactions are more comfortable and confidence that the analyst recommendation is more likely to be the "best" option. Overall, males and females rated both MAUD 3 and analyst sessions quite high with respect to all five self-report questions.

Quality and Size of Attribute Set

Data on the relative size and quality of MAUD 3 and analyst elicited attribute sets is presented in Table 5. Percentages for the size of attributes were based on a simple count.

TABLE 4

Subjects' Impressions of MAUA Sessions

Question	Sex			
	Male (N=13)		Female (N=22)	
	M > A	A > M	M > A	A > M
Brought out new aspects?	39%	39%	18%	64%
Felt comfortable?	8%	46%	23%	46%
Helped to solve problem?	31%	39%	18%	68%
Would trust to find best alternative?	18%	69%	18%	50%
Would use again?	46%	15%	14%	64%

Note: The proportion of subjects rating MAUD 3 higher than analyst (M > A) and the proportion rating the analyst higher than MAUD 3 (A > M) sum to less than one, since some subjects assigned equal ratings.

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Insert Table 5 about here

Percentages for completeness, independence, and quality were generated as follows. For each subject and each criterion, the ratings were scored as favoring MAUD 3 if all three raters gave MAUD 3 attributes a higher rating or if two gave a higher rating and one rated MAUD 3 and the analyst the same. The ratings were counted as favoring the analyst if the consensus was in the analyst's favor. The middle column shows the percentage of cases in which no such decision could be made and therefore indicates the amount of rater disagreement.

As the first row of Table 5 indicates, analysts elicited more attributes than MAUD 3 for the majority of subjects, particularly when the analyst interaction occurred first. There was almost perfect rater agreement on which attribute set was more complete, somewhat less consensus on the issue of independence, and substantial disagreement in judgments of overall quality. Analyst attribute sets were more often judged more complete than MAUD 3 sets, especially if the analyst session preceded the MAUD 3 session. Both logical and value independence depended upon the order of the MAUA sessions. The MAUD 3 attributes were more often judged more independent for subjects exposed to the analyst interaction first, but subjects interacting with MAUD 3 prior to an analyst were split about evenly as to attribute independence. Finally, judgments of overall attribute quality heavily favored analyst elicitations, regardless of the session order.

The attribute set features considered in Table 5 were highly related. In particular, the attribute set of each pair with the

TABLE 5

Site and Quality of Attribute Sets*

Attribute Set Features	Session Order					
	MAUD 3 first (N=24)			Analyst first (N=11)		
	M > A	?	A > M	M > A	?	A > M
# of Attributes	22%	17%	61%	9%	9%	82%
Completeness	22%	17%	61%	9%	0%	91%
Logical Independence	26%	39%	35%	64%	27%	9%
Value Independence	39%	26%	35%	64%	27%	9%
Overall Quality	13%	43%	44%	18%	36%	46%

*The column (?) gives the percentages of cases in which raters disagreed or in which MAUD 3 tied the analyst.

greater number of dimensions was overwhelmingly chosen as being more complete, less independent, and of higher quality than the other attribute set. Ordinal judgments of overall quality were virtually identical to those of completeness.

DISCUSSION AND CONCLUSIONS

MAUD 3 and the analyst sessions produced highly convergent multiattribute utilities. This finding is consistent with Fryback, Gustafson, and Rose's (Note 7) report of MAUAs for evaluating the severity of ischemic heart disease. They presented data suggesting that MAUA model results are quite insensitive to widely varying problem formulations (i.e., attribute structures), assessment settings, and experts. However, we did find that multiattribute utilities were more sensitive to the problem structure than to weight parameter assessments. Differences in MAUD 3 and analyst attributes and single-dimension values, and changes in subjects' values over the intervening week, accounted for more variation in model values than importance weights. This result confirms many empirical and analytical findings of the insensitivity of multiattribute utilities to weights.

Subject's agreement with the MAUD 3 and analyst utilities differed little across session orders, problem types, analysts, or subject sex and race. Assessed weights produced multiattribute utilities in more agreement with holistic judgments than did equal weights. Holistic ratings tended to agree with the most contiguous model values; repeated holistic ratings tended to converge toward agreement with utilities calculated from the models. Unfortunately, it is somewhat difficult to interpret convergence or the lack of it directly as an indicator of the quality of the analysis. Low convergence could mean that the analysis has totally gone awry, or it could be indicative of a deeper, more valid evaluation than the subject is capable of in his/her own holistic ratings.

Our subjects became quite involved in both MAUD and analyst sessions. Subjective ratings of both sessions were greatly skewed toward the high end. Subjects were highly motivated, and their responses seemed more thoughtful and considered than is our experience with thought experiments employing hypothetical scenarios, typical of laboratory experiments with college subjects.

Our sex differences with respect to user satisfaction are curious. One interpretation is that our male subjects possibly had more experience with or aptitude for computer-like tasks. Our impression of the subjects, based on an admittedly brief experience, does not support this hypothesis, however. Yet another explanation lies in a possible analyst sex/subject sex interaction effect; all but one of the analysts was male. Future experiments should certainly better counterbalance for the sex of both subject and analyst.

The median number of attributes elicited was greater for analyst sessions (7.5)than for MAUD 3 sessions (5.9); however, one analyst averaged 10 attributes per session, while another averaged only a little over 5. The 10-attribute analyst was rated higher than the other four analysts in terms of subjects' impressions of the session, but received the lowest amount of acceptance of the resulting alternative orderings. The five-attribute analyst, however, received the lowest subjective ratings of all, but achieved the greatest degree of acceptance of final alternative orderings. Our findings seem to indicate that subjects feel better taken care of when more attributes are included in the analysis, but that subjects' holistic ratings are better accounted for by analyses with smaller rather than larger numbers of attributes.

Our findings regarding the size and quality of attribute sets suggest that our analysts' notions about attribute elicitation are much like those of our subjects: the more the better. Although MAUD 3 elicited smaller, less "complete" attribute sets, they were judged to be more independent, both logically and valuewise. This result is presumably due, at least in part, to the effectiveness of the MAUD 3 mechanism for identifying statistically related attributes and presenting them for combination under a single heading.

Of course, our findings cannot be interpreted in a vacuum. Proper consideration should be given to the subject population, problem types, analyst experience and method (SMART), and the particular MAUA software we employed (MAUD 3). In particular, we should comment on the peculiarities of the MAUD 3 program. We found that MAUD 3 is not truly "stand alone". Many of our subjects asked for assistance in the attribute elicitation phase of the program. Typical mistakes included: repetition of attributes (up to 15 times); including more than one attribute in a given attribute definition; and thinking about other attributes when specifying the "ideal point" and/or scale values on an attribute. MAUD 3 should give the subject more information concerning attribute elicitation, as the "difference questions" are simply too abstract and nondirective.

We also found that very few subjects were able to answer the brlt question properly. Most subjects had initial difficulties understanding this question, and even after careful instructions they experienced some problem keeping track of the different pieces of information that constitute brlts. There also appeared to be a response bias that is built into the sequencing of the brlt questions. That sequence reduces the attractiveness of the gamble until the sure thing is either preferred to or indifferent to the gamble. Subjects, inclined to stop an obviously difficult information processing task, appeared to choose the sure thing even before they reached their indifference point.

In spite of these problems, the computer sessions compared quite favorably with the analyst sessions. This general result is encouraging for those who see the future of decision analysis in computerized and possibly stand-alone decision aids. We conceptualize the development of computerized decision aids in a 3-dimensional framework: (1) The extent to which the program requires the services of someone knowledgeable of either DA or the operation of the program; (2) The degree to which available problem structures are organized into empty DA categories vs. orientation toward problem specific structures that make use of prototypical features generic to all problems of a given class; and (3) The complexity and data base availability of the modeling approach. (Buede, Note 8, calls (3) the engineering science-clinical art dimension of decision aiding.)

The results of our experiment suggest that stand-alone decision aids are feasible. We believe that many of the issues corresponding to problem structuring and option invention can be eliminated by creating generic problem structures, complete with a general structure and a set of options that can be both pruned and added to. We feel that user satisfaction was largely mediated by the fact that our analysts could recommend options and objectives to the decision maker directly, whereas MAUD 3 could not. Perhaps user confidence would be enhanced further by including a problem related data base, thus allowing the subject to employ as complex and complete a model of the choice problem as seems desirable.

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FOOTNOTES

1. All too often, value experiments utilize hypothetical scenarios that more resemble problem-solving tasks, inviting the subject to play a "numbers-game" in which consistency is the winning move. Consequently, many experiments that employ decision analytic value models in assessing a role-played preference structure never come close to any evaluative or affective construct, so necessary to the usual notion of value.

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